ANALYTIC FORMULATION OF THE PRINCIPLE OF INCREASING PRECISION WITH DECREASING INTELLIGENCE FOR INTELLIGENT MACHINES

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ABSTRACT

Intelligent Machines, like Intelligent Robots are capable of performing autonomously in uncertain environments, and have imposed new design requirements for modern engineers. New concepts, drawn from areas like Artificial Intelligence, Operations Research and Control Theory, are required in order to implement anthropomorphic tasks with minimum intervention of an operator. This work deals with the analytic formulation the Principle of Increasing Precision with Decreasing Intelligence; the fundamental principle of Hierarchically Intelligent Control. A three level structure representing the Organization, Coordination and Execution has been developed as a probabilistic model of such a system and the approaches necessary to implement each one of them on an intelligent machine are discussed. The Principle is derived also from a probabilistic model and can be expressed in terms of entropies. It is compatible with the current formulation of the Hierarchically Intelligent Control problem, the mathematical programming solution of which minimizes the total Entropy. The derivation and design of parallel architectures for Artificial Intelligence, like the Boltzmann machine is obtained from such formulation.

1. INTRODUCTION

In our present technological society, there is a major need to build machines that would execute intelligent tasks operating in uncertain environments with minimum interaction with a human operator. Although some designers have built smart robots, utilizing heuristic ideas, there is no systematic approach to design such machines in an engineering manner.

Recently, cross–disciplinary research from the fields of computers, systems, AI and information theory has served to set the foundations of the emerging area of the Design of Intelligent Machines (Saridis, Stephanou 1977).

Since 1977 Saridis has been developing a novel approach, defined as Hierarchical Intelligent Control, designed to organize, coordinate and execute anthropomorphic tasks by a machine with minimum interaction with a human operator. This approach utilizes analytical (probabilistic) models to describe and control the various functions of the Intelligent Machine structured by the intuitively defined principle of Increasing Precision with Decreasing Intelligence (IPDI) (Saridis 1979).

This principle, even though resembles the managerial structure of organizational systems (Levis 1988), has never been established on a scientific basis. Since there is no such reference in the existing literature and its concept represents new ideas not found in the main stream of thoughts of the investigators in the area, this principle needs to be researched and if possible an analytic explanation should be obtained to be consistent with the development of the theory of Hierarchically Intelligent Control.

The impact of such an investigation will be in the engineering design of intelligent robots, since it will provide analytic techniques for universal production (blueprints) of such machines.

In order to accomplish this, some mathematical theory of the intelligent machines will be first outlined. Then some definitions of the variables associated with the principle, like machine intelligence, machine knowledge, and precision will be made. A list of such definitions is given in the section that follows. (Saridis, Valavanis 1988). Then an analytic procedure to establish the principle on a scientific basis is hereby developed.

2. THE MATHEMATICAL THEORY OF INTELLIGENT CONTROLS

In order to design intelligent machines that require for their operation control system with intelligent functions such as simultaneous utilization of a memory, learning, or multilevel decision making in response to "fuzzy" or qualitative commands, Intelligent Controls have been developed by Saridis (1977, 1983). They utilize the results of cognitive systems research effectively with various mathematical programming control techniques (Birk & Kelley, 1981).

Cognitive systems have been traditionally developed as part of the field of artificial intelligence to implement, on a computer, functions similar to one encountered in human behavior (Albus 1975, Minsky 1972, Winston 1977, Nilsson 1969, Pao 1986). Such functions as speech recognition and analysis, image and scene analysis, data base organization and dissemination, learning and high-level decision making, have been based on methodologies emanating from a simple logic operation to advances reasoning as in pattern recognition, linguistic and fuzzy set theory approaches. The results have been well documented in the literature.

Various pattern recognition, linguistic or even heuristic methods have been used to analyze and classify speech, images or other information coming in through sensory devices as part of the cognitive system (Birk & Kelley 1981). Decision making and motion control were performed by a dedicated digital computer using either kinematic methods, like trajectory tracking, or dynamic methods based on compliance, dynamic programming or even approximately optimal control (Saridis and Lee 1979).

The theory of Intelligent Control systems, proposed by Saridis (1979) combines the powerful high-level decision making of the digital computer with advanced mathematical modeling and synthesis techniques of system theory with linguistic methods of dealing with imprecise or incomplete information. This produces a unified approach suitable for the engineering needs of the future. The theory may be thought of as the result of the intersection of the three major disciplines of Artificial Intelligence, Operations Research and Control Theory. This research is aimed to establish Intelligent Controls as an engineering discipline, and it plays a central role in the design of Intelligent Autonomous Systems.

Intelligent control can be considered as a fusion between the mathematical and linguistical methods and algorithms applied to systems and processes. In order to solve the modern technological problems that require control systems with intelligent functions such as simultaneous utilization of a memory, learning, or multilevel decision making in response to "fuzzy" or qualitative commands. Intelligent Control is the process of implementation of an Intelligent Machine and would require a combination of "machine intelligent functions" for task organization purposes with system theoretic methods for their execution.

The control intelligence is hierarchically distributed according to the Principle of Increasing Precision with Decreasing Intelligence (IPDI), evident in all hierarchical management systems. They are composed of three basic levels of controls even though each level may contain more than one layer of tree-structured functions (Figure 1):

1. The organization level.
2. The coordination level.
3. The execution level.

The Organization Level is intended to perform such operations as planning and high level decision making from long term memories. It may require high level information processing such as the knowledge based systems encountered in Artificial Intelligence. These require large quantities of knowledge processing but require little or no precision.

The functions involved in the upper levels of an intelligent machine are imitating functions of human behavior and may be treated as elements of knowledge-based systems. Actually, the activities of planning, decision making, learning, data storage and retrieval, task coordination, etc. may be thought of as knowledge handling and management. Therefore, the flow of knowledge in an intelligent machine may be considered as the key variable of such a system.

Knowledge flow in an intelligent machine's organization level represents respectively (Figure 2):

1. Data Handling and Management.
2. Planning and Decision performed by the central processing units.
3. Sensing and Data Acquisition obtained through peripheral devices.
4. Formal Languages which define the software.

Subjective probabilistic models or fuzzy sets are assigned to the individual functions. Thus, their entropies may be evaluated for every task executed. This provides an analytical measure of the total activity.

Artificial Intelligence methods also applicable for the processing of knowledge and knowledge rates of the organization level of an intelligent machine have been developed by Meystel (1985) and his colleagues.

The Coordination Level is an intermediate structure serving as an interface between the organization and execution level (Figure 3).

It is involved with coordination, decision making and learning on a short term memory, e.g., a buffer. It may utilize linguistic decision schemata with learning capabilities defined in Saridis and Graham (1984), and assign subjective probabilities for each action. The respective entropies may be obtained directly from these subjective probabilities.

The Execution Level executes the appropriate control functions. Its performance measure can also be expressed as an entropy, thus unifying the functions of an "intelligent machine".

Optimal control theory utilizes a non-negative functional of the states of a system in the states space, and a specific control from the set of all admissible controls.to define the performance measure for some initial conditions $(x(t), t)$, representing a generalized energy function. Minimization of the energy functional yields the desired control law for the system.

For an appropriate density function $p(x, u(x,t), t)$ satisfying Jaynes' Maximum entropy principle (1957), it was shown by Saridis (1988) that the entropy for a particular control action $u(x,t)$,

$$H(u) = \int_{\Omega_x} p(x, u(x,t), t) ln p(x, u(t), t) dx$$

is equivalent to the expected energy or cost functional of the system. Therefore, minimization of the entropy $H(u)$ yields the optimal control law of the systems.

This statement establishes equivalent measures between information theoretic and optimal control problems and unifies both information and feedback control theories with a common measure of performance. Entropy satisfies the additive property, and any system composed of a combination of such subsystems can be optimized by minimizing its total entropy. Information theoretic methods based on entropy may apply (Conant 1976).

Since all levels of a hierarchical intelligent control can be measured by entropies and their rates, then the optimal operation of an "intelligent machine" can be obtained through the solution of mathematical programming problems.

An important development of this theory is a structure of the "nested hierarchical" systems (Meystel, 1985). Even when the hierarchy is not tree-like, still using hierarchy is beneficial since the hierarchy of resolutions (errors per level) helps to increase the effectiveness of the system under limited computing power which is important to mobile systems.

The various aspects of the theory of hierarchically intelligent controls may be summarized as follows:

<u>The theory of intelligent machines may be postulated as the mathematical problem of finding the right sequence of decisions and controls for a system structured according to the principle of increasing precision with decreasing intelligence (constraint) such that it minimizes its total entropy.</u>

The above analytic formulation of the "intelligent machine problem" as a hierarchically intelligent control problem is based on the use of entropy as a measure of performance at all the levels of the hierarchy. It has many advantages because of the tree-like structure of the decision making process, and brings together functions that belong to a variety of disciplines. The complete development of this theory and its integration with the other theoretical issues of the Intelligent Autonomous System is the main task of this paper.

3. KNOWLEDGE FLOW AND THE PRINCIPLE OF IPDI

The concept of entropy used in this paper may be generalized if one introduces theory of evidence for the cases that Intelligent Machines are endowed with judgment, a very human property.

What remains to investigate about the general concepts of Intelligent Control Systems are the fundamental notions of Machine Intelligence, Machine Knowledge, its Rate and Precision. The following definitions are useful in order to derive the principle of IPDI.

Def. 1 **Machine Knowledge is defined to be the structured information acquired and applied to remove ignorance or uncertainty about a specific task pertaining to the Intelligent Machine.**

Knowledge is a cumulative quantity accrued by the machine and cannot be used as a variable to execute a task. Instead, the Rate of Machine Knowledge is a suitable variable.

Def. 2 **Rate of Machine Knowledge is the flow of knowledge through an Intelligent Machine.**

Intelligence is defined by the American Heritage Dictionary of the English Language (1969) as: Intelligence is the capacity to acquire and apply knowledge.

In terms of Machine Intelligence, this definition may be modified to yield:

Def. 3 **Machine Intelligence (MI) is the variable (source) which operates on a data-base (DB) of events to produce flow of knowledge (RK)**

One may directly apply the Law of Partition of Information Rates of Conant (1976) to analyze the functions of intelligence within the activities of an Intelligent Control System.

On the other hand, one may define Precision as follows:

Def. 4 **Imprecision is the uncertainty of execution of the various tasks of the Intelligent Machine.**

and

Def. 5 **Precision is the complement of Imprecision, and represents the complexity of a process.**

Analytically, the above relations may be summarized as follows:

Knowledge (K) representing a type of information may be represented as

$$K = -\alpha - lnp(K) = (\text{Energy}) \tag{1}$$

where $p(K)$ is the probability density of Knowledge.

From equation (1) the probability density function $p(K)$ satisfies the following expression in agreement with Jaynes' principle of Maximum Entropy (1957):

$$p(K) = e^{-\alpha - K}; \quad \alpha = ln \int_X e^{-K} dx \tag{2}$$

The Rate of Knowledge R which is the main variable of an intelligent machine with discrete states is

$$R = \frac{K}{T} = (\text{Power})$$

It was intuitively thought (Saridis 1983). that the Rate of Knowledge must satisfy the following relation which may be thought of expressing the principle of Increasing Precision with Decreasing Intelligence

$$(MI):(DB) \longrightarrow (R) \tag{3}$$

A special case with obvious interpretation is, when R is fixed, machine intelligence is largest for a smaller data base e.g. complexity of the process. This is in agreement with Vamos' theory of Metalanguages (1986).

It is interesting to notice the resemblance of this entropy formulation of the Intelligent Control Problem with the ε–entropy formulation of the metric theory of complexity originated by Kolomogorov (1956) and applied to system theory by Zames (1979). Both methods imply that an increase in Knowledge (feedback) reduces the amount of entropy (ε–entropy) which measures the uncertainty involved with the system.

An analytic formulation of the above principle derived from simple probabilistic relation among the Rate of Knowledge. Machine Intelligence and the Data Base of Knowledge, is presented in the next section. The entropies of the various functions come naturally into the picture as a measure of their activities.

4. THE ANALYTIC FORMULATION OF THE IPDI

In order to formulate mathematically the concepts of knowledge–based systems, one must consider the state space of knowledge Ω_s with states $s_i, i = 1, 2, \ldots n$. They represent the state of events at the nodes of a network defining the stages of a task to be executed.

Then knowledge between two states is considered as the association of the state s_i with another state s_j and is expressed as

$$K_{ij} = \frac{1}{2} w_{ij} s_i s_j \tag{4}$$

where w_{ij} are state transition coefficients, which are zero in case of inactive transmission.

Knowledge at the state s_i is the association of that state with all the other active states s_j and is expressed as

$$K_i = \frac{1}{2} \sum_j w_{ij} s_i s_j \tag{5}$$

Finally, the total knowledge of a system is considered as

$$K = \frac{1}{2} \sum_i \sum_j w_{ij} s_i s_j \tag{6}$$

and has the form of energy of the underlying events. The rate (flow) of knowledge is the derivative of knowledge and for the discrete state space Ω_s is defined respectively

$$R_{ij} = \frac{K_{ij}}{T} \quad , \quad R_k = \frac{K_i}{T} \quad , \quad R = \frac{K}{T} \tag{7}$$

where T is a fixed time interval.

Since knowledge was defined as structured information, it can be expressed by a probabilistic relation similar to the one given by Shannon, and expressed for each level by equation (1):

$$lnp(K_i) = -\alpha - K_i \tag{8}$$

which yields a probability distribution satisfying Jaynes' Principle of Maximum Entropy (for $E\{K\} = G$)

$$p(K_i) = e^{-\alpha_1 - K_i} \qquad e^{\alpha_1} = \sum_i e^{-K_i}$$

The rate of knowledge is also related probabilistically by considering that $K_i = R_i T$.

$$p(R_i) = p(R_i T) = e^{-\alpha_1 - TR_i} = e^{-\alpha_1 - \mu_1 R_i} \tag{9}$$

The principle of Increasing Precision with Decreasing Intelligence is expressed probabilistically by

$$PR(MI, DB) = PR(R) \tag{10}$$

where MI is the machine intelligence and DB is the data base associated with the task to be executed and represents the complexity of the task which is also proportional to the precision of execution. The following relation produces

$$\begin{aligned} &P(MI, DB) = P(R) \\ &P(MI/DB)\,P(DB) = P(R) \\ &lnp(MI/DB) + lnp(DB) = lnp(R) \end{aligned} \tag{11}$$

Taking the expected value on both sides

$$H(MI/DB) + H(DB) = H(R) \tag{12}$$

where $H(x)$ is the entropy associated with x. For a constant rate of knowledge which is expected during the conception and execution of a task increase of the entropy of DB requires a decrease of the entropy of MI for the particular data base, which manifests the IPDI. If MI is independent of DB then

$$H(MI) + H(DB) = H(R) \tag{13}$$

In the case that $p(MI)$ and $p(DB)$ satisfy Jaynes' principle as $p(R)$ does

$$\begin{aligned} p(MI/DB) &= e^{-\alpha_2 - \mu_2 MI_{DB}} \\ p(DB) &= e^{-\alpha_3 - \mu_3 DB} \end{aligned} \tag{14}$$

where α_i and $\mu_i, i = 2, 3$ are appropriate constants.
Then the entropies are rewritten as

$$-\alpha_2 - \mu_2 MI_{DB} - \alpha_3 - \mu_3 DB = -\alpha_1 - \mu_1 R \tag{15}$$

and if

$$\alpha_1 = \alpha_2 + \alpha_3 \qquad \gamma_2 = \frac{\mu_2}{\mu_1}, \quad \gamma_3 = \frac{\mu_3}{\mu_1}$$

then

$$\gamma_2 MI_{DB} + \gamma_3 DB = R \tag{16}$$

which represents a specific but more explicit version of the Principle of Increasing Precision with Decreasing Intelligence.

This Principle is applicable both across one level of the Intelligent Hierarchy as well as throughout the levels of the Hierarchy, in which case the flow R represents the throughput of the system in an information theoretic manner. The partition law of information rate applies naturally to such a system.

The entropy of DB may be related to ε–entropy as follows: A system requiring certain (n) level of precision takes n–times the data base DB required for a simple precision. But

$$H(nDB) = E\{lnn\} + E\{lnDB\} \tag{17}$$

where $E\{lnn\}$ is the ε–entropy associated with the complexity of execution. A case study demonstrating the validity of the above is given in Saridis and Valavanis (1988).

5. A CASE STUDY: THE DERIVATION OF THE BOLTZMANN MACHINE

In the current literature of parallel architectures for Artificial Intelligence, the Boltzmann machine represents a powerful architecture that allows efficient searches to optimally obtain the combination of certain hypotheses of input data and constraints (Fahlman, Hinton, Sejnowski 1985).

The Boltzmann architecture may be interpreted as the machine that searches for the optimal interconnection of several nodes representing different primitive events in order to produce a string defining an optimal task. Such a device may prove extremely useful for the design of the upper levels of an intelligent machine (Saridis and Valavanis 1988).

Associating each independent event with a binary random variable $x_i \epsilon \{0,1\}$, with apriori probabilities $p(x_i = 1) = p_i$, $p(x_i = 0) = l - p_i$, where 1 represents inclusion, and 0 represents exclusion of the ith event from the string one defines the energy of flow of knowledge between nodes (events) i and j by

$$R_{ij} = \frac{1}{2} v_{ij} x_i x_j \tag{18}$$

with probability

$$p(R_{ij}) = E\left\{e^{-\alpha_j - R_{ij}}\right\} = \sum e^{-\alpha_j - \frac{1}{2} v_{ij} x_i x_j} \tag{19}$$

where v_{ij} are the transfer coefficients and $v_{ii} = 0$ $i = 1, \ldots n$ as in eq. (4) and (7).

Using the values of the binary variables the expection in (19) yields

$$\begin{aligned} p(R_{ij}) &= e^{-\alpha_j - \frac{1}{2} v_{ij}} p_i p_j + e^{-\alpha_i} p_i (1 - p_j) + e^{-\alpha_i} p_j (1 - p_i) + e^{-\alpha_i} (1 - p_i)(1 - p_j) \\ &= e^{-\alpha_j} \left[1 - (1 - e^{-\frac{1}{2} v_{ij}}) p_i p_j\right] \end{aligned} \tag{20}$$

where

$$e^{\alpha_j} = \sum_i \left[1 - (1 - e^{-\frac{1}{2}v_{ij}})p_i p_j\right]$$

The probability of flow at node j is given by

$$\begin{aligned} p(R_j) &\doteq E\left\{e^{-\alpha-R_j}\right\} = \sum e^{-\alpha-\frac{1}{2}\sum_i v_{ij}x_i x_j} p(x_i) \\ &= e^{-\alpha}\left[\sum\prod_i e^{\frac{1}{2}v_{ij}x_i x_j} p(x_j)p(x_i)\right] = e^{-\alpha}\left[\prod_i (1 - (1 - e^{-\frac{1}{2}v_{ij}})p_i p_j\right] = \\ &= \prod_i p(R_{ij}) \end{aligned} \tag{21}$$

Similarly, one derives the probability of the total flow of knowledge R for a particular sequence of events (connection of the network):

$$P(R) = \prod_i p(R_i) = \prod_{ij} p(R_{ij}) \tag{22}$$

The entropy associated with the above distribution is

$$H(R) = \psi + E\{R\} \tag{23}$$

may serve as the cost criterion to be minimized at the search for optimal connection of the primitive events and where τ and ψ is a normalization constant.

This analytic derivation yields the mechanism of a Boltzmann machine as defined by Hinton and Sejnowski (1986). The only difference is that knowledge considered as energy is assumed here to be symmetric e.g. with no potential term, which is present in biological systems. The above probabilities may be used to escape local minima during the search, for the optimal string.

The search for the optimal connectiveness may be reassigned to find the interconnection that yields minimum entropy (23).

Learning may be obtained by adjusting the coefficients v_{ij}, and apriori probabilities after the completion of a task for t times, by using the recursive expression

$$\begin{aligned} v_{ij}(t+1) &= v_{ij}(t) + \rho_{t+1}\left[\xi - v_{ij}(t)\right]; \\ p_i(t+1) &= p_i(t) + \rho_{t+1}\left[\xi - p_i(t)\right]: \end{aligned} \tag{24}$$

where

$$\xi = \begin{cases} 1 & \text{when task is successful} \\ 0 & \text{when is not} \end{cases}$$

and

$$\rho_{t+1} = \frac{1}{t+1} \qquad \text{the harmonic sequence.}$$

Convergence of this algorithm is guaranteed in Saridis and Graham (1984).

The principle of IPDI is immediately applied to find the amount of Machine Intelligence needed for a flow of knowledge R.

$$H(R) = H(MI) + H(DB) \tag{25}$$

where DB is related to the number of primitive events n, e.g. its ε–entropy, and reflects the complexity of the system. For minimum $H(R)$ and fixed $H(DB)$ e.g., number n of primitive events, the Machine Intelligence required is also minimum.

Example

Consider a system of four primitive events (nodes), represented by the directed graph of Figure 4, where e_1 (node 1) the root e_2 (node 2) is the transitive event and e_3 (node 3) and e_4 (node 4) are the leaves. There are four possible connections between the root and the leaves, since the graph is directed (1–3), (1–2–3), (1–2–4) and (1–4), to which the flows of knowledge correspond to

$$R_{31} = R_{21} = R_{41} = R_{32} = R_{42} = R_{34} = R_{43} = 0$$

and from (20)

$$p(R_{12}) = 1$$

$$p(R_{13}) = \frac{1 - [1 - \exp\left(-\frac{1}{2}v_{13}\right)]p_1p_3}{2 - [1 - \exp\left(-\frac{1}{2}v_{13}\right)]p_1p_3 - \left[1 - \exp\left(-\frac{1}{2}v_{23}\right)\right]p_2p_3}$$

$$p(R_{23}) = \frac{1 - \left[1 - \exp\left(-\frac{1}{2}v_{23}\right)\right]p_2p_3}{2 - \left[1 - \exp\left(-\frac{1}{2}v_{13}\right)\right]p_2p_3 - \left[1 - \exp\left(-\frac{1}{2}v_{23}\right)p_2p_3\right]}$$

$$p(R_{24}) = \frac{1 - \left[- \exp\left(-\frac{1}{2}v_{24}\right)\right]p_2p_4}{2 - \left[1 - \exp\left(-\frac{1}{2}v_{14}\right)\right]p - 1p - 4 - \left[1 - \exp\left(-\frac{1}{2}v_{24}\right)\right]p_2p_4}$$

$$p(R_{14}) = \frac{1 - \left[1 - \exp\left(-\frac{1}{2}v_{14}\right)\right]p_1p_4}{2 - \left[1 - \exp\left(-\frac{1}{2}v_{14}\right)\right]p_1p_4 - \left[1 - \exp\left(-\frac{1}{2}v_{24}\right)\right]p_2p_4}$$

The total probabilities for each of the four possible connections are

$$\begin{aligned} p(R_{13}) &= p(R_{13}) \\ p(R_{123}) &= p(R_{12})p(R_{23}) = p(R_{23}) \\ p(R_{124}) &= p(R_{12})p(R_{24}) = p(R_{24}) \\ p(R_{14}) &= p(R_{14}) \end{aligned}$$

Using the following values the following probabilities result

$$p_1 = 1 \quad , \quad p_2 = p_3 = p_4 = 0.5$$

$$v_{13} = 0.4\ ,\ v_{23} = 0.6\ ,\ v_{24} = 0.2\ ,\ v_{14} = 0.1$$

$$p(R_{13}) = 0.410$$
$$p(R_{123}) = 0.590$$
$$p(R_{124}) = 0.594$$
$$p(R_{14}) = 0.406$$

The total entropies are

$$H(R_{13}) = 0.795 + 0.041 = 0.836$$
$$H(R_{123}) = 0.795 + 0.0885 = 0.8835$$
$$H(R_{124}) = 0.877 + 0.0594 = 0.9364$$
$$H(R_{14}) = 0.877 + 0.0203 = 0.8973$$

The search for minimum entropy yields that the connections $(1 \rightarrow 3)$ results in the optimum connection of the system.

The weights $v_{13}, v_{23}, v_{24}, v_{14}$ and the apriori probabilities p_2, p_3 and p_4 may be upgraded after a successful execution of the task using algorithm (24).

6. APPLICATION TO ROBOTIC SYSTEMS

The principle of Increasing Precision with Decreasing Intelligence has direct application to the design of Intelligent Machines. It provides a means of structuring hierarchically the levels of the machine. Since for a passive task the flow of knowledge through the machine must be constant, it assigns the highest level with the highest machine intelligence and smallest complexity (size of data base), and the lowest level with the lowest machine intelligence and largest complexity. Such a structure agrees with the concept of most organizational structures encountered in human societies. Application to machine structures is straight forward.

Even at the present time there is a large variety of applications for intelligent machines. Automated material handling and assembly in an automated factory, automated inspection, sentries in a nuclear containment are some of the areas where intelligent machines have and will find a great use. One of the most important applications though is the unmanned space exploration where, because of the distances involved, autonomous anthropomorphic tasks must be executed and only general commands and reports of executions may be communicated.

Such tasks are suitable for "intelligent robots" a type of intelligent machines capable of executing anthropomorphic tasks in unstructured uncertain environments. They are usually designed in a human-like shape and are equipped with vision and other tactile sensors to sense the environment, two areas to execute tasks and locomotion for appropriate mobility in the unstructured environment. The controls of such a machine are performed according to the theory of Intelligent Machines previously discussed, (Saridis and Stephanou, 1977), (Saridis 1983, 1985a, 1985b), (Meystel 1985, 1986). The three levels of controls, obeying the Principle of Increasing Precision with Decreasing Intelligence, are implemented with appropriately selected feedback, as shown in Figure 5, for a PUMA 600 robot arm with sensory feedback.

The Boltzmann machine architecture may be used to implement the organization level of an intelligent robot by considering the proper interconnection of primitive events represented by nodes and the coordination level of an intelligent robot by appropriately connecting the various coordinators to the dispatcher for communications purposes, as in Figure 5.

7. CONCLUSIONS

A mathematical theory for intelligent machines was proposed and traced back to its origins. The methodology was developed to formulate the "intelligent machine", of which an intelligent robot system is a typical example, as a mathematical programming problem as using the aggregated entropy of the system as its performance measure. The levels of the machine structured according to the Principle of Increasing Precision with Decreasing Intelligence can adopt performance measures easily expressed as entropies. This work establishes an analytic formulation of the Principle, provides entropy measures for the account of the underlying activities, and integrates it with the main theory of "Intelligent Machines". Optimal solutions of the problem of the "intelligent machine" can be obtained by minimizing the overall entropy of the system. The entropy formulation presents a tree-like structure for this decision problem very appealing for real-time computational solutions.

This formulation was proved to be applicable to the derivation and design of parallel architectures for Artificial Intelligence. The Boltzmann machine was analytically derived from the definitions of knowledge flow and Jaynes' principle of maximum entropy. The optimal event (node) connection has been obtained by searching for a minimum of the entropy criterion and the IPDI has been directly applicable.

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REFERENCES

Albus, J. S., (1975, "A New Approach to Manipulation Control: The Cerebellar Model Articulation Controller". *Transactions of ASME, J. Dynamics Systems, Measurement and Control, 97,* 220-227.

Birk, J. R. and Kelley, R. B., (1981, "An Overview of the Basic Research Needed to Advance the State of Knowledge in Robotics", *IEEE Trans. on SMC,* SMC–11, No. 8, pp. 575–579.

Conant, R. C., (1976), "Laws of Information Which Govern Systems". IEEE Trans. on SMC, SMC–6, 4, 240–255, April 1976.

Fahlman, S. E., Hinton, G. E., Sejnowski, T. J. (1983). "Massively Parallel Architectures for AI: NETL, THISLE and Boltzmann Machines", Proceedings of National Conference on AI, Menlo Park, CA.

Fu, K. S., (1971), "Learning Control Systems and Intelligent Control Systems: An Intersection of Artificial Intelligence and Automatic Control", *IEEE Trans on Automatic Control,* Vol. AC–16, No. 1, 70–72.

Hayes–Roth, et al., (1983), *Building Expert Systems,* Addison–Wesley, New York.

Hinton, G. E., Sejnowski, T. J. (1986). "Learning and Relearning in Boltzmann Machines", pp. 282–317, in *Parallel Distributed Processing*, ed. D. E. Rumelhart and J. L. McClellan, MIT Press.

Jaynes, E. T., (1957), "Information Theory and Statistical Mechanics". *Physical Review*, 106, 4.

Kolmogorov, A. N., (1956), "On Some Asymptotic Characteristics of Completely Bounded Metric Systems", Dokl Akad Nank, SSSR, Vol. 108, No. 3, pp. 385–9.

Levis, A., (1988) "Human Organizations as Distributed Intelligence Systems", Proceedings 1st IFAC/IMACS Symposium on Distributed Intelligent Systems, Varna, Bulgaria.

Meystel, A., (1985), "Intelligent Motion Control in Anthropomorphic Machines", Chapter in *Applied Artificial Intelligence,* S. Andriole Ed. Pentrocellis Books, Princeton, NJ.

Meystel, A., (1986), "Cognitive Controller for Autonomous Systems", *IEEE Workshop on Intelligent Control 1985*, p. 222, RPI, Troy, New York.

Minsky, M. L., (1972), *Artificial Intelligence*, McGraw–Hill, NY.

Nilsson, N. J., (1969), "A Mobile Automation: An Application of Artificial Intelligence Techniques", *Proc. Int. Joint Conf. on AI*, Washington, D. C.

Pao, Y.–H., (1986), "Some Views on Analytic and Artificial Intelligence Approaches", *IEEE Workshop on Intelligent Control*, p. 29, RPI, Troy, NY.

Saridis, G. N., (1977), *Self-organizing Controls of Stochastic Systems*, Marcel Dekker, New York, New York.

Saridis, G. N., (1979), "Toward the Realization of Intelligent Controls", *IEEE Proceedings*, Vol. 67, No. 8.

Saridis, G. N., (1983), "Intelligent Robotic Control", *IEEE Trans. on AC–29,* 4.

Saridis, G. N., (1985a), "Intelligent Control–Operating Systems in Uncertain Environments", Chapter 7 in *Uncertainty and Control*, J. Ackermann Editor, Springer–Verlag, Berlin, pp. 215–233.

Saridis, G. N., (1985b), "Control Performance as an Entropy", *Control Theory and Advanced Technology*, 1, 2.

Saridis, G. N., (1985c), "Foundations of Intelligent Controls". *Proceedings IEEE Workshop on Intelligent Controls,* p. 23, RPI, Troy, NY.

Saridis, G. N., (1988), "Entropy Formulation of Optimal and Adaptive Control", IEEE Transactions on AC, Vol. 33, No. 8, pp. 713–721.

Saridis, G. N. and Graham, J. H., (1984), "Linguistic Decision Schemata for Intelligent Robots", *Automatica*, Vol. 20, No. 1, 121–126.

Saridis, G. N. and Lee, C. S. G., (1979), "Approximation of Optimal Control for Trainable Manipulators", *IEEE Trans. on SMC*, Vol. SMC–8, No. 3.

Saridis, G. N., Stephanou, H. E., (1977), "A Hierarchical Approach to the Control of a Prosthetic Arm", *IEEE Trans. on SMC,* Vol. SMC–7, No. 6, pp. 407–420.

Saridis, G. N. and Valavanis, K. P., (1988), "Analytical Design of Intelligent Machines", *Automatica the IFAC Journal.* Vol 24, No2 pp 123-33

Shannon, C., Weaver, W., (1963). *The Mathematical Theory of Communications*, Illini Books.

Stephanou, H. E., (1986). "Knowledge Based Control Systems", *IEEE Workshop on Intelligent Control 1985*, p. 116, RPI, Troy, New York.

Valavanis, K. P., (1986). "A Mathematical Formulation for the Analytical Design of Intelligent Machines", Ph.D. Thesis, Technical Report RAL No. 85, Dept. of ECSE, Rensselaer Polytechnic Institute, Troy, New York.

Vamos, T., (1986). "Metalanguages – Conceptual Models. Bridge Between Machine and Human Intelligence", Working paper E/37, Hungarian Academy of Science.

Winston, P. (1977). *Artificial Intelligence*, Addision–Wesley, New York.

Zames, G., (1979). "On the Metric Complexity of Causal Linear Systems, ϵ–entropy and ϵ-dimension for Continuous Time". *IEEE Trans. Automat. Control*, Vol. AC–124, pp. 222–230, April.

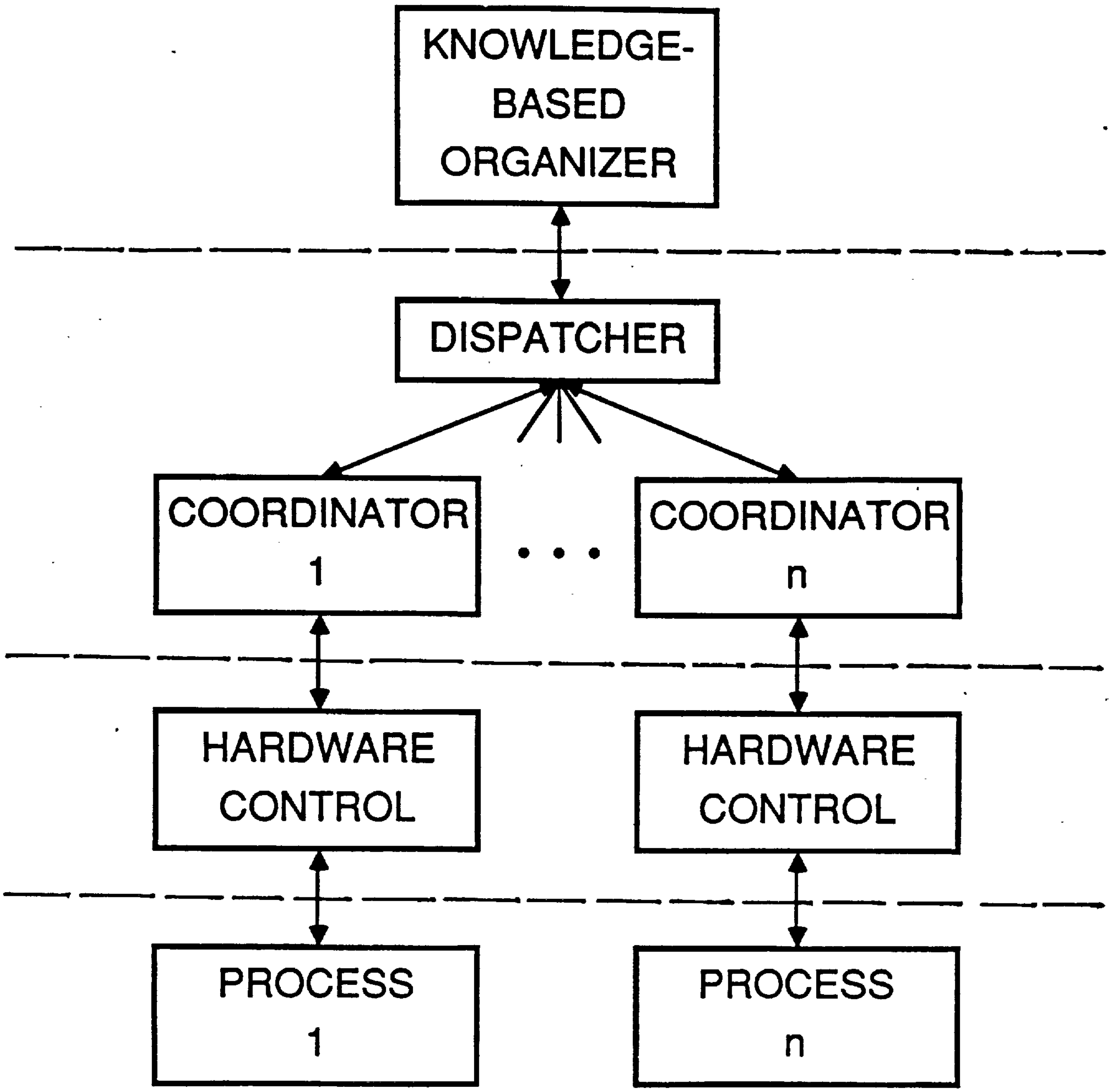

Figure 1. Hierarchical Intelligent Control System

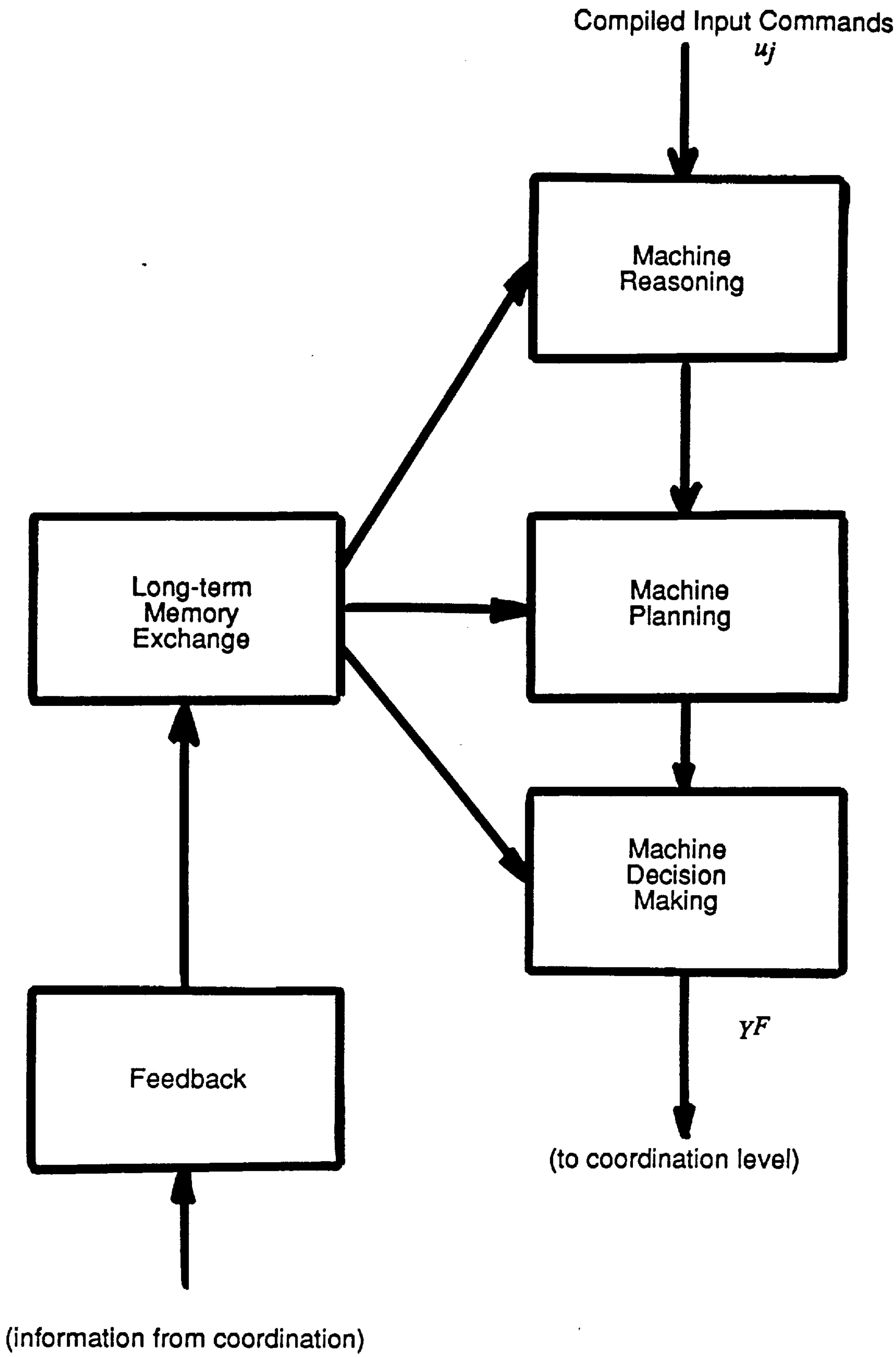

Figure 2. Block Diagram of the Organization Level

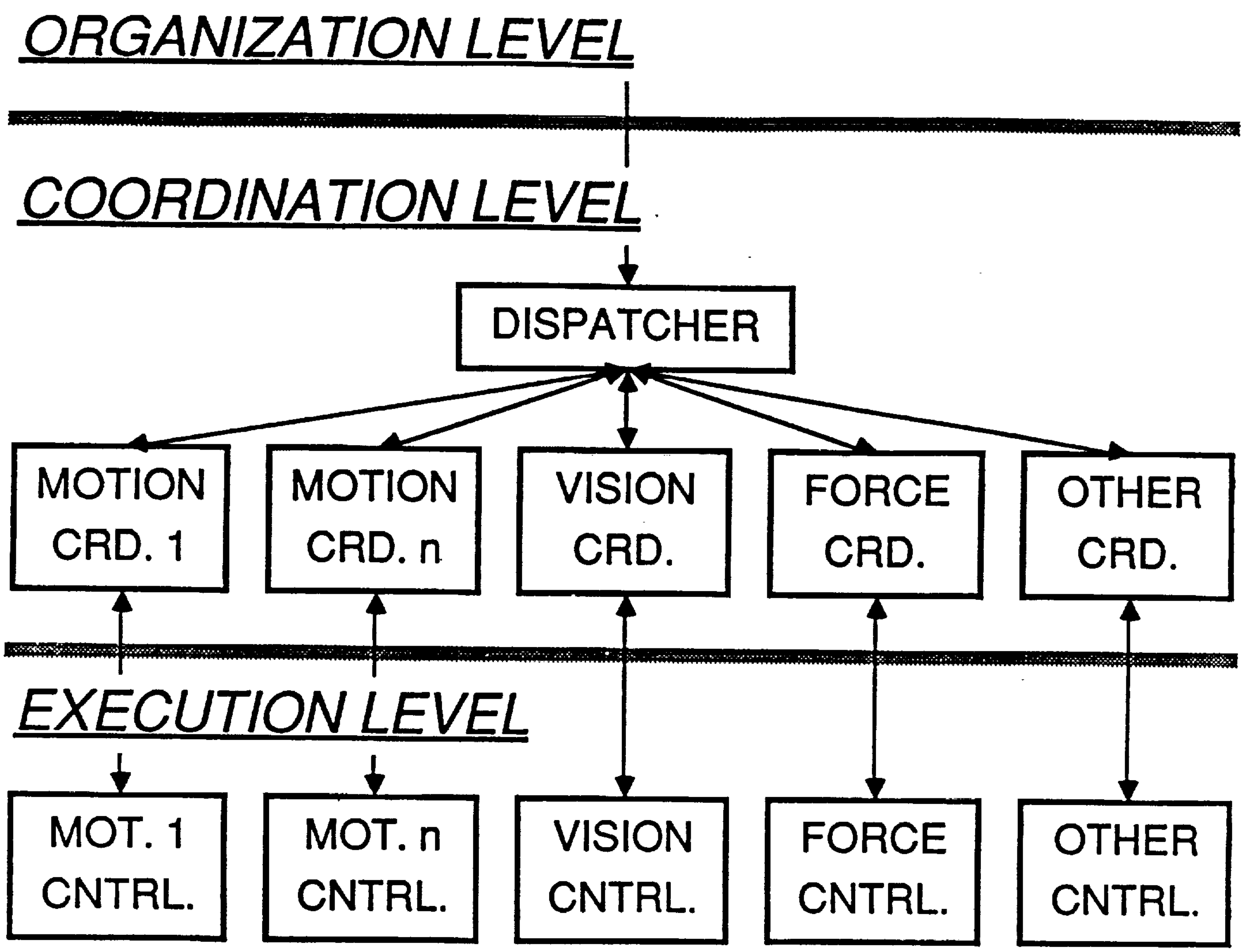

Figure 3. Hierarchical Intelligent Manipulator Control System

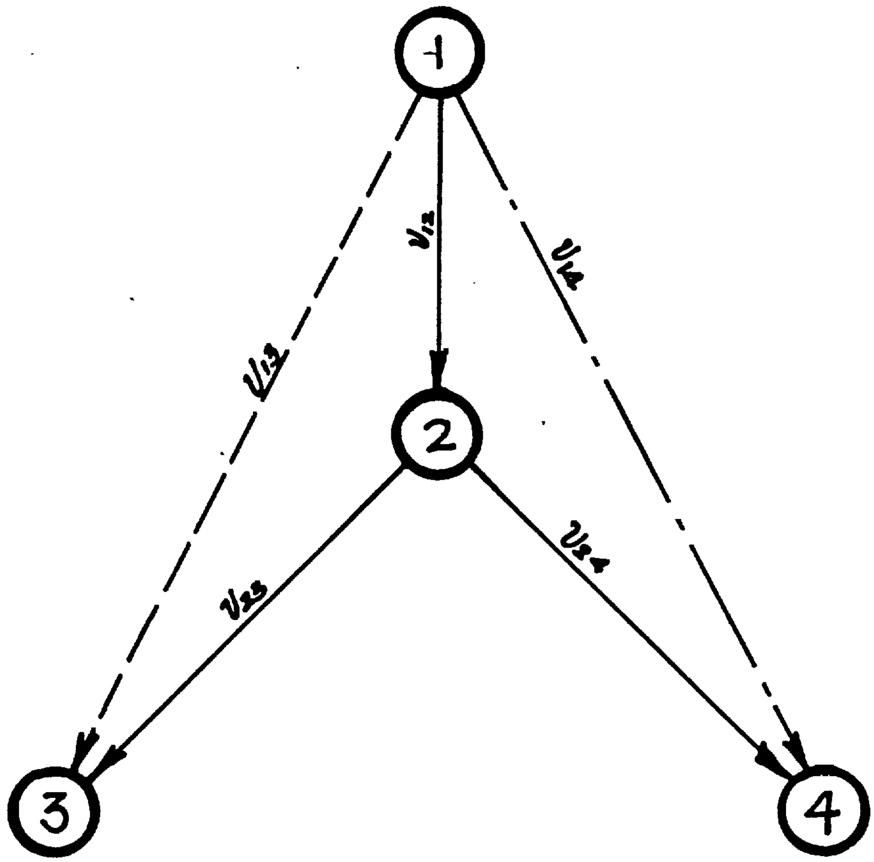

Figure 4. The directed network of the example

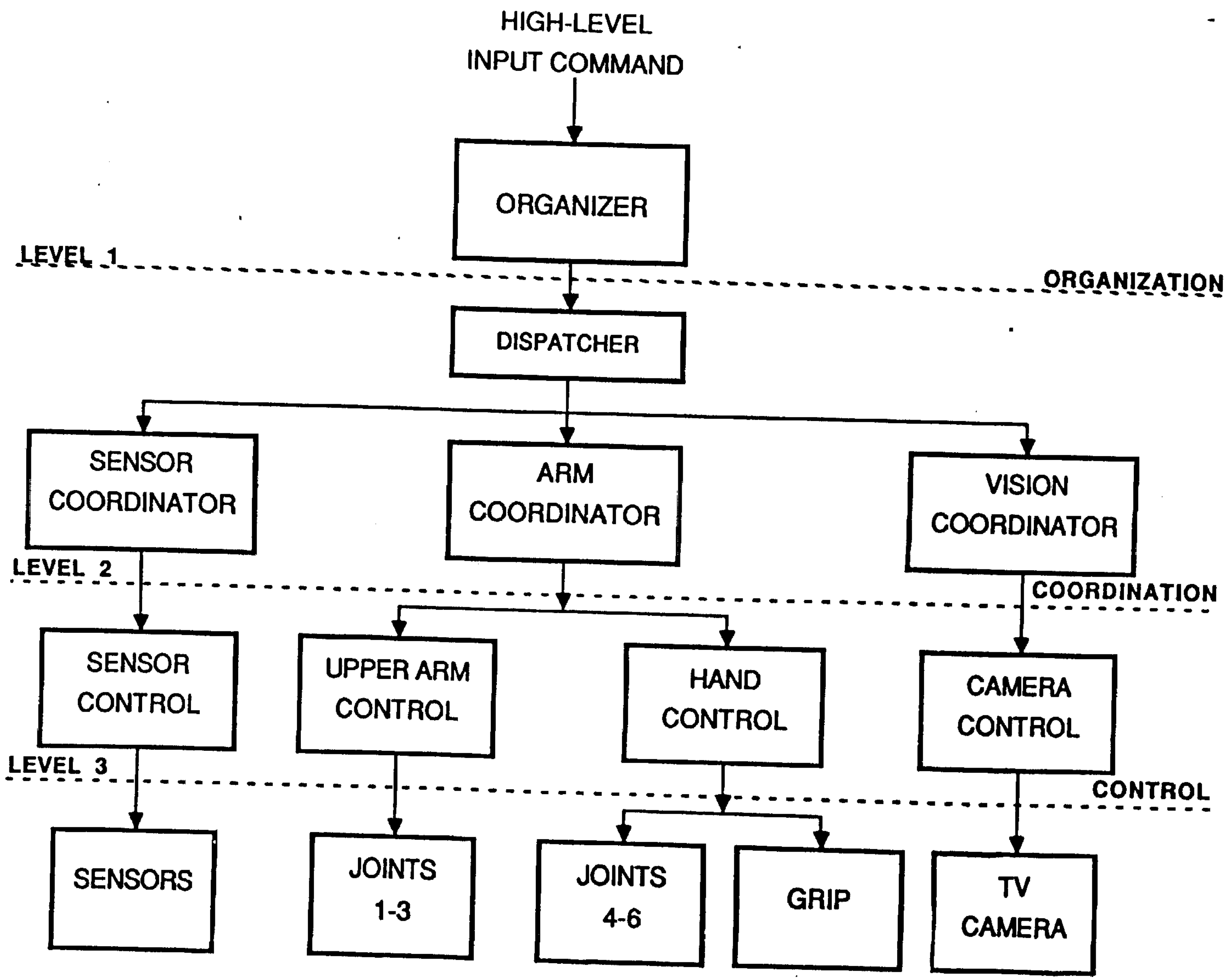

Figure 5. Hierarchically Intelligent Control for a Manipulator with Sensory Feedback